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Towards personalized educational resources recommendations for teachers

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Abstract. Recommender systems experience the challenging and complex process of finding educational resources recommendations for teachers which requires a careful awareness of the teacher's context. These systems should take into consideration the contextual coexistence of teachers in multiple environments or contexts such as social, working, and sentimental contexts. The collected data for each of these contexts is assembled from different sources and systems with different data architectures. Accordingly, this paper provides a multi-step proposition towards a personalized educational resource recommendations for teachers. Furthermore, the paper discusses the data sources from which the contextual data is collected, in addition to the purposed methodology for integrating and mapping the data into the ontology. At the end, the paper illustrates the importance and the role of the teacher analytics and the sentimental data in this proposition. The proposed approach results in a complete representation of the teacher's context and hence, the personalized recommendations.

Keywords: recommender systems, education, ontology, teacher

1 Introduction

Recommender systems (RSs) filter information to predict user's preferences towards a specific item. Through this process, it imitates how the social exchange of recommendations works. During the 90s and 00s, RSs were developed mainly for commercial applications [15]. In an educational context, RSs can provide personalized recommendations of learning resources based on each user's details and interests [25]. Recommendations can be personalized with the help of the complete context description for each user and in our case, teachers. Context description can be defined differently according to the research point-of-view and the predefined actors related to this context. Each research point-of-view tends to provide its own unique individualistic perspective which can be completely

different from other research fields concerning the same context actors. Also in the educational field, context can be defined from different point-of-views: geography, educational institution structure, learner, or teacher. Since this research focuses on educational resources recommendations for teachers, we limit our scope to teacher’s context in terms of profile, demography, level of teaching, experiences, social environment, cultural background, and working environment [16].

In this paper, we propose an approach to provide personalized educational resources recommendations for teacher. The proposed approach introduces a context-aware methodology for the recommendations using an ontology-based educational data integration [20]. The approach covers multiple contexts of a teacher, such as living, working [19], and sentimental contexts [21]. The remaining of this paper is organized as follows: Section 2 states the current social and scientific challenges in our research. Section 3 explores the related work to this paper. Section 4 introduces the proposed approach and its architecture. Section 5 discusses the usability and the usefulness of this approach with illustrated examples. Finally, section 6 summarizes and concludes this paper and provides its perspectives.

2 Problem Statement

A context-aware recommendation can be achieved through a proper definition of the existing problem. At the beginning, teacher contexts must be selected according to the relation with the teaching/learning performance. Between the social representation and the multiple identities of a teacher, we can summarize the teacher’s coexistence into the following identities: a living/cultural identity and a working/institutional identity. Identities are a way of providing an explanation of meanings and experiences of a certain person based on cultural attributes that are interrelated with other forms of meanings [6]. These meanings are inseparable when it comes to the associated context with a certain identity, such as a teacher’s identity definition. Other contexts are said to be in a continuous process of reconstruction due to the dynamicity of this entity with the surrounding conditions. One of these contexts is the sentimental context of a person and more precisely, the teacher’s sentimental wellbeing [17]. Therefore, we need to identify the effective contexts for a teacher taking into consideration living and working environments in addition to the sentimental state.

A two-pronged solution is needed in this case by well-represented of the multiple contexts of a teacher in addition to the data integration and processing according to these contexts. A teacher coexists in multiple contexts in real-life such as living context, working context and sentimental context. The solution must consider the well-representation of all contexts as well as the integration process between them. For well-representation, each of the three contexts must be defined at the beginning. The living context is described as the birth envi-

ronment in which the teacher was born and raised and the living environment where he lives during the current moment. The working context is represented as the working conditions in the educational institution where the teacher works in addition to the living conditions of the area demographically and geologically. The sentimental context can be defined as the emotional status of the teacher during the daily life which is affected by multiple stimuli [22]. Mood can perfectly describe the explainable and unexplainable affective states simultaneously [11]. In order to provide context-aware recommendation, all the previously mentioned contexts should be carefully described and represented for smooth data treatment.

Ontology representation solves the first scientific challenge as it provides an enhanced visualization of data and relationships in addition to the context sharing between multiple information systems. Another problem arises during the integration of the contexts because of the different formats and schemas of the collected data from each context. For an optimal integration of data, we need to discover all the available data concerning our cause and then, to identify the relevant ones. On the other hand, the discovered data will be meaningless if it was not analyzed, and insights were extracted. Therefore, it can be said that data integration challenge results into two sub-challenges: discovery and exploitation [13]. A probable solution is the ontology-based data integration providing uniqueness of data and facilitating the data insertion and retrieval. Integrating these two approaches can present a sufficient solution for the discussed problems.

3 Related Work

The related research to this paper, is divided into two categories of research to address the two parts of the proposed two-pronged solution. The first category is the educational data integration and the data modeling unification targeting the educational resources. The second category is the context-related educational ontologies and its related educational resources recommender systems.

3.1 Educational Data Integration

The educational data integration approaches have multiplied during the past decade targeting the different data categories. The review conducted by Desmarais et al., explores the data modeling and integration approaches from the learner’s point-of-view [8]. Through this review, it was noticed that none of the reviewed models was targeting the teacher’s point-of-view. Dhekne et al. introduced a new Massive Open Online Courses (MOOC) aggregation from different providers [9]. The similar approach was followed by Ambite et al. to link and index training resources using a unified data model [3]. The latest research that was done by Duran et al. [10], integrates open educational resources (OERs)

from various sources that are related to Computing and Electronics engineering field using RDF and ontology representation. We can observe the lack of educational data integration research from the teacher point-of-view.

3.2 Educational Ontologies and Ontology-based Recommender Systems

The research on the context representation in the educational domain had common interests in the learner point-of-view or the administrative structure of the educational institution. The systematic review conducted by Costa et al. [7], shows the significant amount of research directed towards the educational context in terms of learning analytics and context description. The teacher context is almost absent from the reviewed papers. For example, Guettat et al. introduced a computational domain ontology to profile the student/learner and the corresponding relation with the learning resources only without any mention of the teacher's interconnecting relationship in this context [14]. While the research conducted by Antonelli et al., implements an ontology to represent an open network platform for higher education [5]. The teacher was placed in this ontology from the learning outcomes perspective only and the authors illustrated the relation between the expected learning outcomes, the learning process, and the learners without further linkage to any contextual concepts.

The state-of-the-art article by Stancin et al. [23], reviewed more than 90 ontologies in the educational context that were published between 2015 and 2019, none of these ontologies was constructed from the teacher's point-of-view. Ibrahim et al. implemented three educational ontologies: course, student, and job ontologies [18]. The teacher and the contextual representation were absent from the three introduced ontologies. Another remarkable ontology from Stancin review, is the ontology created by Fuchs et al. [12]. This ontology represents learners, learning content, and learning semantics and it does not represent neither the learners' context nor the relationship with their teacher/instructor.

The comprehensive review performed by Tarus et al. [24], collects the ontology-based recommender systems in the educational domain from 2005 until 2014. Most of the reviewed journal papers targeted learners or the educational system in general and the used ontologies were from the learner or the system point-of-view. We conclude that the research in the educational domain lacks concentration on the teacher point-of-view. Therefore, research is needed in the context description ontologies for teacher as well as the ontology-based data integration in the same domain.

4 Approach Architecture

The proposed recommender system model consists of multiple steps as shown in Fig. 1. During the first step, the data is collected and integrated from multiple relational data sources. These data sources have various formats with different structure levels from multiple origins. When data is collected and integrated from different sources, it reflects the dispersed contexts of the teacher in a more precise description and observations. Data integration techniques, such as conflict resolution function and cosine similarity, prevents data redundancy and conflictions. Four datasets were integrated into one data collection to represent the living and working contexts of the teacher. As for the learning resources, another six datasets were integrated from different data sources and with different formats.

Through the second step, the relationally integrated data is mapped to the ontology. Ontology is a formal representation of a conceptualization of a certain domain that provides explicit domain assumptions. Also, the ontology facilitates the knowledge sharing among multiple sub-systems, as well as the reusability, communication, and collaboration. The proposed ontology is constructed based on the teacher’s multiple contexts and his preferences; teacher profile, learner profile, living environment and working environment. The third and fourth steps concern with the hybrid recommender engine, and the filtering and sorting of the resulting recommendations. The fifth step of this proposal deals with the teacher behaviors and interactions with the system. The direct interactions with resources, concepts, and knowledge sharing are recorded for each teacher using the MEMORAE SoIS platform [1]. However, the indirect interaction through the teacher’s sentimental state (mood), are captured using the Moodflow@doubleYou platform [4]. The mood is detected according to the 3-level classification approach: positive, negative, and neutral. The teacher’s interactions and mood act as the user feedback to resort and filter the provided list of recommendations from the fourth step. The emotion-based data introduces a new dimension of personalization and draws the system’s attention to new insights of teacher’s preferences. Therefore, the recommender system can provide the teacher with enjoyable resources, and it can evaluate the recommendations correctly.

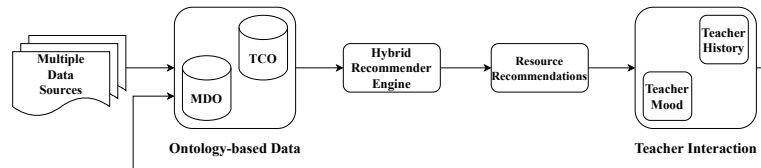


Fig. 1. Block diagram of the model architecture

4.1 Ontology-based Data

Teachers coexist in multiple contexts which leads to a data extraction process from multiple sources with different architecture and formats. These different sources can be divided into four main categories: educational resources, personal information, environmental data, and educational institutional data as shown in Fig. 2. All the data categories were integrated and mapped into the different ontologies [20]. Only one category was not covered in the mentioned work, the personal data, which is collected during real-time interaction of a teacher with an educational recommender system.

Afterwards, the integrated data is mapped into the integrated ontologies: Teacher-Context Ontology (TCO), MEMORAE ontology, and Mood Detection Ontology (MDO) [19, 21]. The three ontologies extend one another to complete the full representation of a teacher’s context as shown in Fig. 3. TCO represents teacher coexistence in three different contexts: work environment, living environment, and educational institution, while MDO provides a sentimental state representation within the teacher-resource interactivity. These interactivities, which are part of the integration between TCO and MEMORAE (MCC) ontologies, affects the teacher’s mood and therefore, his working performance. On the other hand, MCC ontology represents the user account and knowledge sharing within an organization which enforces the activities tracking and placement within the teacher’s context. These integrated contextual concepts are used by the hybrid recommender engine to provide personalized educational resources’ recommendation to the targeted teacher.

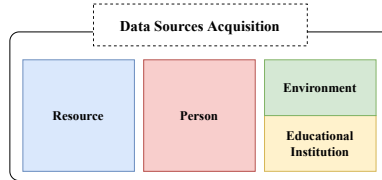


Fig. 2. Data categories in teacher context

4.2 Hybrid Recommender Engine

Ontology-based recommender engines are defined as knowledge-based recommender engines that replace the relational data representations with the ontology semantic representation for items and users [2]. In this proposition, the knowledge-based engine processes the search query provided by the teacher and evaluates the resulting list according to the teacher’s profile and previous activities. The cosine similarity function calculates the relative score for each feature-search parameter couple and afterwards as in Equation 1 where R_a is a search

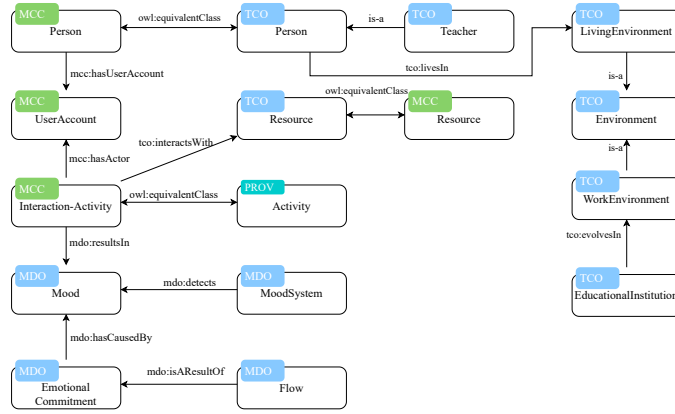


Fig. 3. TBox Ontology representation of the multiple teacher contexts

list and R_b is a previously rated resource for all n resource descriptive features, the Pearson utility function evaluates each feature's importance to this specific teacher[?]. The resulting list of recommendation is forwarded to the filtering and sorting algorithm to reevaluate the recommendations with respect to the context-aware recommender engine.

$$Sim(R_a, R_b) = \frac{\sum_{i=1}^n (R_{ai} R_{bi})}{\sqrt{\sum_{i=1}^n R_{ai}^2} \sqrt{\sum_{i=1}^n R_{bi}^2}} \quad (1)$$

The context-aware recommender engine is responsible for matching a teacher's contextual situation with another teacher. But at the beginning, the engine extracts the contextual dimensions/factors for a certain teacher and initiates the teacher-teacher matching process. These dimensions/factors are dependent on the person's situation which prevents the unification of the selected factors. Moreover, predictions of context-aware recommender systems, can be imprecise if all contextual factors were weighted equally. The personalized process of weighting and selection of contextual factors improves the recommendations' quality according to each teacher. Therefore, the proposed approach introduces a methodology to weight and select contextual factors relevant to a certain teacher's context.

The Semantic Web Rule Language (SWRL) is a rule markup language that is used with Ontology Web Language (OWL) to express logical rules into readable syntax. In this approach, SWRL rules are used to sort the teachers' peer list generated from both recommender engines. For each teacher, the rules are applied to reason the ABox instance corresponding to him. A total score is calculated by counting the number of satisfied rules. Then, the list of resources' recommendations is sorted according to a descending order of the obtained scores. At the

end, the teacher is asked to view and interact the recommended resources. The mood of the teacher is detected during the interaction process and is used to evaluate further recommendations process.

5 Discussion

The ABox representation of the novice teacher, Jean, is illustrated in Fig. 4. The teacher contexts representation along with the sentimental feedback empower both recommender engines. The knowledge-based engine uses the teacher's profile information and searches for resources/items match. In our example, Jean, who speaks French and obtained an engineering degree, is searching for a course about "Numeric analysis", therefore, one of the recommended resources is the French course, "Analyse numérique". On the other hand, the context-aware engine extracted and weighted the context factors and then, finds another teacher similar to Jean's context. The engine finds that most similar teachers speak French, and they coexist in similar working and living environments. Also, the context-aware engine includes the "Analyse numérique" course within the resulting recommendations list. Finally, the sorting reasoning algorithm scores this course with the highest obtained score. When the resource was viewed by Jean, he was satisfied by the recommended course which is proved by the generated positive mood. Therefore, the extensive contextual representation of the teacher opens new possibilities to grant a full-usability opportunity for recommender engines. Accordingly, the hybrid recommender engine will provide each teacher with personalized and precious educational resources' recommendations.

6 Conclusion and Perspectives

This paper summarizes multiple novel propositions in the process of introducing personalized recommendations to teachers. A new data collection and integration approach is discussed, in addition to a data mapping to the ontology. Teacher analytics collection and sentimental analysis methods are illustrated to monitor the interactions with the given recommendations. We believe that none of the previous research provided an extensive discussion of the recommendation-generation process for teachers as well as their context description. For the future work, we need to validate the experimental efficiency of the proposed approaches with a hybrid recommender system.

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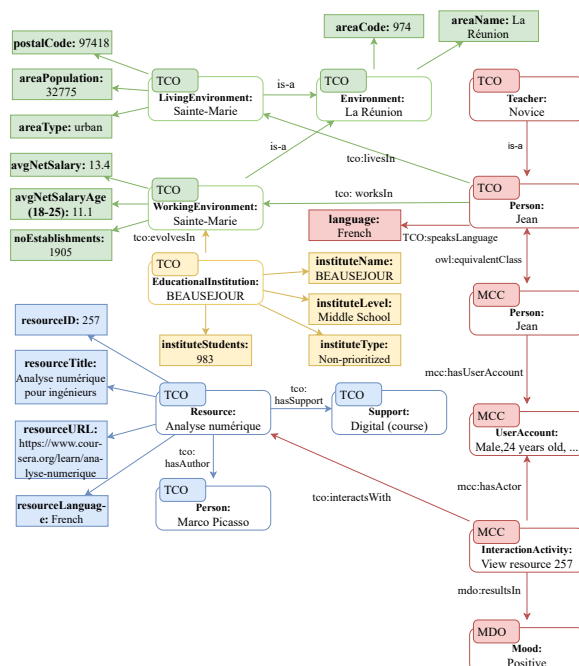


Fig. 4. An ABox ontology example

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